

Once upon a time: Understanding team processes as relational event networks

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Abstract

For as long as groups and teams have been the subject of scientific inquiry, researchers have been interested in understanding the relationships that form within them, and the pace at which these relationships develop and change. Despite this interest in understanding the process underlying the unfolding of relationships in teams, current theoretical and operational formulations of team process require greater specificity if they are to truly afford a high-resolution understanding. Most researchers interested in team process, study it as either a snapshot, or as a limited series of snapshots, rather than as a continuous movie displaying the nuanced sequential interactions unfolding among varying subsets of team members. Given the increasing availability of rich data regarding team dynamics, corresponding advances are needed in conceptual and analytic frameworks to utilize continuous-time data to further our understanding of team processes. This paper identifies four challenges that hinder the identification of team process/dynamics and elaborates a theoretical approach with the associated analytic machinery needed to advance a truly time-sensitive understanding of team process.

Keywords

Longitudinal data, relational event network analysis, social networks, team dynamics, team process

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For as long as groups and teams have been the subject of scientific inquiry, researchers have been interested in understanding the relationships that form within them, and the pace at which those relationships develop and change. Tuckman's (1965) oft-cited work on group development—the four stages of forming, storming, norming, and performing—permeated both popular and scientific thinking about groups for more than six decades (despite limited empirical support). In the 1970s and 1980s, group researchers shifted from descriptive to normative models of interaction processes (Hackman, 1987), largely based on the still popular input–process–outcome model (IPO; McGrath, 1964). An unfortunate side effect of much of the research that followed the IPO tradition is that its attention to causal drivers of team effectiveness took precedence over the study of how team member interactions unfold over time. This is remarkable, since the conversion of inputs to output will almost always take *time* (hence the need to take a temporal/dynamic point of view), be nonlinear, and its success will likely depend on exactly *how* the team carries out the conversion—prompting the need to study the exact sequence of interactions within the team.

More recently, there has been widespread enthusiasm about the need to reincorporate time into our thinking about groups and teams (cf. Arrow, 1997; Harrison, Mohammed, McGrath, Florey, & Vanderstoep, 2003; Ilgen, Hollenbeck, Johnson, & Jundt, 2005; McGrath & Argote, 2001). In their seminal paper on team processes, Marks, Mathieu, and Zaccaro's recurring phase model (2001) advanced thinking about group dynamics; time was put back into team interaction by detailing the processes that are needed in different phases or episodes of completing a task. A team process is defined as the behavioral interaction that occurs among members of the team enabling them to integrate their task activities toward the attainment of a group goal. The Marks et al. (2001) taxonomy details 10 such processes, occurring at different points in time as teams pursue their goals.

The essence of how we think about time in teams is revealed in both our conceptual and operational definitions of team process. The prevailing view of time in teams conceptualizes team process (i.e., the sequence of unfolding interactions within the team) as homogenous interactions among members (i.e., a compositionally emergent phenomenon; Kozlowski & Klein, 2000). The focus is on the type of interaction that occurs without regard to who in the team engages in it. Hence investigations of teams over time tend to take the theoretical approach that the entire team *as an aggregate* is changing over time—for example, if the focal team process is coordination, a time-based approach might consider how the team as a whole improves or degrades its degree of coordination. This compositional view of team process impedes understanding by aggregating team interactions across time and members (Kozlowski & Klein, 2000). In contrast, a compilational or patterned view of team process is needed (Crawford & LePine, 2013).

We accomplish this in four sections. First, we discuss the challenges for accurately characterizing temporal conceptualizations of team process. Second, we present a temporal-based framework for thinking about processes in teams as a temporal sequence of relational events. Third, we describe a statistical model designed to enable researchers to study the unfolding of relational events in teams and, fourth, provide a brief empirical illustration.

Part I: Challenges on the way to studying team process

Since the earliest research on small groups, there has been an intuition that the nature of group interaction distinguishes effective groups from ineffective ones. More than 50 years of empirical research has built on that intuition. Despite the prevalence of studies that invoke the notion of team process as an explanatory mechanism for team effectiveness, the empirical work linking processes to outcomes is not as

Table 1. Illustrative meta-analytic effect sizes on team IPO relationships.

Author (year)	Type of team relationship meta-analyzed	Effect sizes
Team input "I" → Team outcome "O" relationships		
Bell (2007)	"I" (team composition) → "O" (team performance)	$\rho = .27$ (GMA) $\rho = .25$ (collectivism)
Burke et al. (2006)	"I" (team leader behaviors) → "O" (team effectiveness)	$\rho = .33$ (task leadership) $\rho = .36$ (person leadership)
Salas et al. (2008)	"I" (team training) → "O" (team performance)	$\rho = .39$ (team training)
Team process "P" → Team outcome "O" relationships		
LePine et al. (2008)	"P" (team process) → "O" (team performance)	$\rho = .29$ (transition) $\rho = .29$ (action) $\rho = .29$ (interpersonal)
Mesmer-Magnus & DeChurch (2009)	"P" (information sharing) → "O" (team performance)	$\rho = .50$ (unique IS) $\rho = .32$ (open IS)

Note. ρ = sample size weighted mean observed correlation with corrections as they were applied in the published meta-analysis (e.g., measurement unreliability, attenuation due to dichotomization). GMA = general mental ability. IS = information sharing. This is not meant to be an exhaustive reporting of all of the published meta-analyses. Reviewing the full record is beyond the scope of this paper, and does not show trends that differ from the ones included in this table.

explanatory as one might hope. As an illustration, consider the variance in team effectiveness explained by processes relative to inputs, as reported in the literature to date. Several meta-analyses published in the 2000s show that although team processes are believed to be explanatory of team performance, their effect sizes are generally similar to those of input variables, which begs the question of what "process" is really adding to our understanding of team performance. Notable meta-analytic studies linking inputs to outcomes include Bell's synthesis of surface- and deep-level compositional variables (Bell, 2007), Burke et al.'s synthesis of studies examining the impact of team leader behavior (Burke et al., 2006), and Salas et al.'s synthesis of research on team training (Salas et al., 2008). Characteristic effect sizes from these meta-analyses are presented in Table 1, showing that some of the more impactful team inputs have effect sizes ranging from .25 to .39.

Two meta-analyses were conducted linking team processes to team outcomes, these are shown in the next block of Table 1. LePine, Piccolo, Jackson, Mathieu, Saul (2008) synthesized effect sizes linking group interaction to

outcomes based on the Marks et al. (2001) process taxonomy and reported corrected effect sizes of .29. Mesmer-Magnus and DeChurch (2009) synthesized the group information-sharing literature and found general information-sharing to have an effect size of .32 and unique information-sharing an effect size of .50. If these various processes are adding to our understanding of group effectiveness beyond what we understand from the inputs alone, we might expect that process–outcome relationships would show larger effect sizes than input–outcome effect sizes. Theoretical and/or methodological imprecision may explain why the effect sizes of "process" are modest in comparison to those of "inputs." Next, we briefly discuss four challenges of past research that inform future research on team processes.

Challenge 1: Assuming homogeneity over time

Most studies of team process treat process as being homogeneous over time. This occurs when researchers, even when they observe teams over extensive periods, aggregate process data gathered over time into a summary index

that portrays direct process \leftrightarrow outcome relationships (Marks et al., 2001). Many of our theories are specified as “the more X (e.g., communication) the higher Y (e.g., team performance)” and do not specify whether the effect of X on Y is constant throughout the team’s performance episode or whether some systematic evolution or fluctuation should be expected. Consequently, variance across time is collapsed into a static summary indicator of teamwork, which effectively removes the potential to uncover any temporal effects.

This is particularly unfortunate, because many processes are likely to be subject to some level of path dependence where the influence of a variable at any point in time depends on the current state of the system and its past values. For example, team members who have worked together intensely over the past few weeks may be more likely to share information today than team members who have barely had the need to interact. Path dependence implies that the same phenomenon applied to the same group can have different effects depending on when it happens and what happened before (Cronin, Weingart, & Todorova, 2011). Analyzing process by using summary statistics that assume homogeneity across time rules out the opportunity to take into account the ordering of events and the impact of this order; for example, past conflict followed by collaboration is more likely to lead to high future performance than past collaboration followed by conflict. Assuming homogeneity over time severely limits our opportunity to develop and test time-dependent theories and may result in incomplete at best, and faulty at worst, inferences about the emergence and outcome of group processes.

Challenge 2: Assuming homogeneity across members and their interactions

At the heart of any definition of team process is the interaction among the team’s members. Teams can only function by virtue of the interactions among its constituent members. There

have been some significant efforts to theorize about team interaction. Poole (1981, 1983a, 1983b; Poole & Roth, 1989) developed and empirically tested a sophisticated typology of multiple group decision paths to characterize decision development in small groups. More recently, in their recurring phase model, Marks et al. (2001) offer a taxonomy of 10 processes occurring at different points in time as teams pursue their goals; for example, they propose that planning and goal setting are two processes that occur during the teams’ early stages. Unfortunately, these and related approaches generally aggregate interactions across individuals. The recurring phase model aggregates interactions across the team, without distinguishing if some members of the team might be more likely (or more effective) than other team members to, for instance, initiate planning-related interactions. This clearly matters: planning is often more effective to the extent that team leaders are involved; so it not only matters that planning-related activity occurs, but it also matters which specific team members jointly engage in it. As such, these models are unable to capture variability among teams that might have similar group processes at the aggregate level, but differ in the structural patterning of these group processes between specific team members. As a result, we are unable to explain differences in outcomes that might be caused by this variability.

As team members interact with other members, local (e.g., dyadic or triadic) interactions generate a global interaction pattern. In turn, this global pattern influences individual team members and their local interactions. Over time, local dynamics bring about team-level dynamics that emerge from, and subsequently shape and constrain future local interaction dynamics (Brass, Galaskiewicz, Greve, & Wenpin, 2004; Gabbay & Leenders, 1999; McGrath, Arrow, & Berdahl, 2000).

As Cronin et al. (2011) note, dyadic interaction dynamics can occur at different rates. It is therefore clear that emergent team-level

processes remain incompletely characterized—and hence inadequately understood—without theoretically specifying and empirically testing the role of the specific individuals engaged in the local-level interaction (see Brass et al., 2004, for an extensive treatment of this issue). Hence, similar global-level features might be incorrectly interpreted as emerging from different patterns of local-level interaction (if the specific individuals involved were not taken into account). For example, it is often argued that the extent to which team members share information positively affects team innovation; this can inspire a researcher to correlate average interaction intensity in a team with team innovation. However, a team in which information is shared freely across the team as a whole may be more innovative than a team in which information sharing is largely contained within subgroups, but with the same average team-level intensity. Interaction dynamics will almost always vary across dyads in a team, even in situations when clear interaction norms exist. In sum, we suggest that process-based research should model local-level dynamics with greater specificity allowing for differences in local-level interaction among the team's members and their differential impact on the global team level.

Challenge 3: Assuming that repeated measurements capture team dynamics

Even though we conceptually articulate group processes as occurring in continuous time, empirical studies generally rely on repeated measurements to measure process over time. However, in team research, like in the social sciences in general, theories rarely specify time scales, even though the time scales along which social interaction unfolds vary widely (Butts, 2009). For example, a theory about trust in teams can acknowledge that it takes time for trust to develop (as a function of the repeated interaction among team members), but will generally not specify exactly how long that will

take. This becomes problematic when the researcher attempts to test the relation between past interaction and trust: if the measurements are not taken at the appropriate time scales, the researcher may find no significant association or over- or underestimate the association. Overall, we have very little theory about time lags, feedback loops, and durations, which makes it difficult to know when, for how long, and how often to measure key variables, even when we want to take on a temporal perspective in our analysis (Ancona, Goodman, Lawrence, & Tushman, 2001). The result is that, even when the researcher takes the effort to collect dynamic data, empirical findings are rarely reflective of the actual temporal process. A solution is to measure team process in continuous time rather than at multiple discrete time points. This allows the researcher to track the actual development of the team's process (which is very likely nonlinear and unevenly spaced across time anyway) without having to make arbitrary and largely atheoretical decisions about time intervals.

Challenge 4: Relying on theories of team process that are underdeveloped with regard to time

Using the temporal lens, the study of team process not only lets us consider what team members work on, what they interact about, and how they organize themselves, but it also invites us to think about the antecedents and outcomes of the pace, trajectories, and cyclicity in their interactions. Many of our hypotheses of team processes (typically: "teams higher on X are also higher on Y") are static in formulation—they do not explicitly describe temporal relations between variables nor do they call for longitudinal data to test them. The consequence of this is that many researchers find it challenging to formulate hypotheses that truly capture temporal phenomena and to think in terms of temporal

variables. An example of a temporal variable is the rate of change, as opposed to the static level or intensity of a variable (Cronin et al., 2011). Rates capture speed and pacing: rates are important descriptors of team interaction dynamics. While there are several other fundamentally temporal variables that can be featured in a time-sensitive analysis, rates may be the most basic building block that can inform processual theory and research design.

The challenges we have formulated above also relate to the three dimensions that differentiate teams as suggested by Hollenbeck, Beersma, and Schouten (2012): *skill differentiation* (i.e., the extent to which team members differ in expertise, experience, education, gender, culture, etc.), *authority differentiation* (i.e., the extent to which there is a single leader with decision-making power), and *temporal stability* (i.e., the extent to which a team has a joint history and future). They argue that most team types can be defined by their position along these three dimensions. Our first challenge (“assuming homogeneity over time”) is clearly tied to the “temporal stability” dimension: the assumption of homogeneity over time is more tenuous when there is lower stability in the team’s composition, its environment, and its tasks. For example, so-called “real teams” (Hackman, 2002), where members may work together for as long as 10 years, might be assumed to be fairly homogenous over time. Note, though, that, while this may be the case over the long run, this may not hold for intermittent shorter work episodes. The assumption becomes even more questionable for teams that are inherently less temporally stable, such as project teams, action teams, or advice teams.

Another homogeneity challenge described above (“assuming homogeneity across members and their interactions”) is especially relevant for teams with clear differentiation in skill and/or authority. Teams high in “skill differentiation” (e.g., X-teams, cross-functional teams, or crews) are likely to work with a division of roles and responsibilities, which

undermines the assumption of homogeneity across team members. Similarly, the more members are differentiated with respect to their decision-making authority, the less homogenous the team will be in situations that entail any form of decision-making.

Overall, our main argument is that there is variance to be explained in team process and outcomes and that research can explain more of this variance by focusing on higher resolution conceptualizations of team process—disaggregating interaction over time and across team members. In order to do so, we need to imbue our theories and analyses of team process with more temporal constructs. Such theories and designs need to explicitly focus on processes in continuous time with local (e.g., dyadic) interactions as the fundamental building block. The holy grail for research on team dynamics is to be able to watch a “movie” of team process as it unfolds, then pause the movie, and be able to answer the questions: what will likely happen next and with what implications for outcomes?

Part II: Team process as relational events

One way to handle the four challenges outlined above is to move to a unit of analysis where theory, measurement, and analysis are aligned with this continuous time, movie-like, view of team process. We propose the *relational event* as an appropriate unit of analysis, defined as an interaction initiated by one team member to one or more other team members at a particular point in time.

The use of the term “relational event” originated in the social networks literature (Brandes, Lerner, & Snijders, 2009; Butts, 2008). The naming of the term is somewhat unfortunate in our context as it might suggest a focus on specific interpersonal incidents such as conflict or trust-building among team members. In fact the term refers to every single interaction between any two or more team members at any

Table 2. Example of a potential relational event sequence.

Time	Sender	Receiver	Content of event	Sentiment	Modality
00:01	James	Leila	Provides info on topic A	Positive	Face-to-face
00:05	Leila	Sarah	Requests info on topic B	Neutral	E-mail
00:06	James	Anne	Asks for planning meeting	Neutral	E-mail
00:32	Eddie	Jack + Sarah	Sends working document on task progress	Positive	E-mail
00:53	Sarah	Anne	Talks about weekend	Positive	Face-to-face
01:01	Manager	All	Updates on course of project	Neutral	E-mail
01:10	Eddie	Jack	Asks re: progress on C	Neutral	E-mail
05:12	Eddie	Sarah	Asks re: progress on C	Neutral	E-mail
05:53	Sarah	Leila	Replies to request for info on topic B	Neutral	Phone
06:12	Jack	Eddie	Provides info on progress on C	Neutral	E-mail
07:08	Eddie	Jack	Expresses dissatisfaction re: Jack's performance	Negative	Face-to-face
08:12	Jack	Manager	Asks for managerial support	Positive	Phone

time (e.g., sending an email message, talking at the water fountain, asking someone for guidance, providing social support, or discussing the planning of an activity). A relational event is minimally characterized by the time at which the interaction was initiated, the team member who initiated it, and the team member(s) who were the recipients. A relational event can be further extended to characterize the *content* of the event (e.g., “knowledge-sharing” or “suggesting a planning meeting”), the *function* of the event (e.g., messages related to planning tasks vs. messages related to goal-setting tasks), the *modality* of the event (e.g., sending email or communicating face-to-face), the *valence* of the event (e.g., an event with positive or negative emotion), the *strength* of the event (e.g., its duration or emotional intensity), and so forth. A *sequence of relational events* is represented as a series of time-stamped interactions from one team member to one or more other team members.

When modeling a sequence of relational events, the object of explanation is the *rate* at which a single relational event from one particular team member to one or more other specific team members is likely to occur at any given instance of time, given any prior interaction. As the team progresses over time, rates change (speeding up interpersonal exchanges or slowing them down), and rates of interaction

may vary across dyads within the team (e.g., the interaction between two accountants may be faster paced than that between an accountant and an engineer). Modeling the rates directly enables a researcher to study the rhythm, pacing, speeding, and slowing of exchanges among team members, as a function of team members' relational histories (i.e., path dependence) and preferences. Interactions among team members cumulate to shape dynamics at higher levels (i.e., subgroup, team, multiteam system), which, in turn, can affect the future rate of interaction for a given set of team members. Table 2 provides an example of what a relational event sequence could look like.

Sequential structural signatures (SSS)

In order to develop a time-based view of team process, a useful theoretical notion is the sequential structural signature (SSS). In contrast to many conceptualizations of team process that specify the quality and quantity of a given type of interaction that is needed for the team to accomplish its goals (e.g., coordination or information sharing), SSSs articulate the underlying theoretical mechanism through which team interactions unfold.

Under some mild statistical assumptions, these rates can be expressed as a (time-dependent) log-linear function of SSSs, so that

theorizing about time evolution can occur in much the same way as we think about time-dependent linear models and linear regression. The rate of a relational event from team member *A* to team member *B* at a particular time *t*, can simply be written as (dropping the *A*, *B*, and *t* subscripts for readability):

$$\text{rate} = \exp(\alpha + \theta_1 \text{SSS}_1 + \theta_2 \text{SSS}_2 + \theta_3 \text{SSS}_3 + \dots) \quad (1)$$

which shows the familiar linear form we are accustomed to when we test theories (the exponent is there because rates can be shown to follow an exponential distribution, but this does not affect the structure of the theoretical argument). Equation (1) represent the hypothesis that, for instance, the rate of interaction from *A* to *B* at a particular point in time *t* is a function of a general rate of interaction α (which is equivalent to an intercept), as well as one or more SSSs that characterize distinct patterns of past interaction histories among the team members and their personal characteristics. The θ s (equivalent to regression coefficients) represent the influence of each of these SSSs on the rate of a relational event from *A* to *B*. Next we will discuss several SSSs and discuss exactly how they can be used to articulate the dynamics of relation events in teams.

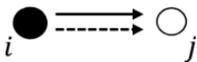
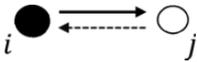
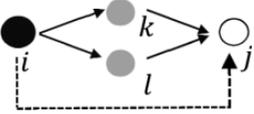
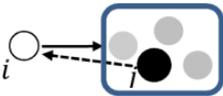
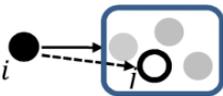
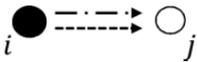
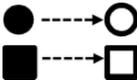
As time progresses (and histories grow), rates will change accordingly. Since a rate is defined as the number of times an event is expected to occur within a given period of time, rates translate naturally to (evolving) length of times between events: when rates increase, the speed of interaction increases, when rates decrease, interaction slows down. Table 3 gives an overview of the SSSs discussed in this paper.

The most straightforward SSS is *inertia*, which posits that the rate of a relational event occurring at any given time from one team member, *A*, to another member, *B*, increases with the volume of the prior instances of a relational event from *A* to *B*. In other words, the more *A* has initiated a relational event (such as a

request for information) to *B* in the past, the higher the rate with which *A* is likely to initiate a request for information to *B* in the immediate future. This SSS captures the routinization/habituation of interaction and derives from the common assumption that people will repeat past behavior and will be more inclined to do so the more they have displayed that behavior in the past. Through repetition, behavior becomes automatic or habitual. The literature lacks agreement on the exact speed by which repetition transforms into habitual behavior and on the exact shape of the relation (Hull, 1943, 1951; Lally, van Jaarsveld, Potts, & Wardle, 2010). However there is general consensus that the greater the number of past repetitions of certain behavioral actions, the stronger the habit formation (Ajzen, 2002) and hence the stronger the team member's tendency to repeat the interaction. A positive parameter for inertia indicates a tendency towards routinizing interaction; a negative parameter shows team members' current preference towards breaking habitual interaction (and hence towards "partner switching").

A slightly more complicated SSS, which we term *reciprocity*, posits that the rate of a relational event occurring at a given time from *A* to *B*, is positively affected by the volume of prior instances of a relational event from *B* to *A*. Reciprocity is a fundamental norm of human interaction (Blau, 1964; Gergen, Greenberg, & Willis, 1980; Sahlins, 1972). Research in the social exchange tradition has shown that individuals engaged in reciprocal exchanges trust their partners more, evaluate them more positively, and feel more committed to them and create the kind of trust that is resilient and affect-based (Molm, Schaefer, & Collett, 2009). This is especially the case when individuals give and reciprocate benefits without negotiation—as in the embedded reciprocal exchanges we discuss here (Molm, 2003). Furthermore, a repeated pattern of reciprocal team–member exchanges can buffer the team against the effects of negative events (de Jong, Curşeu, & Leenders, 2014).

Table 3. Summary of sequential structural signatures.

Name	Visualization	Interpretation	Example
Inertia (or: general inertia)		The tendency of person <i>i</i> to continue to initiate events towards person <i>j</i> , as a function of the volume of past events from <i>i</i> to <i>j</i> .	The more email messages John has sent to Irene, the higher the rate of future email messages from John to Irene.
Reciprocity (or: general reciprocity)		The tendency of person <i>i</i> to initiate events towards person <i>j</i> , as a function of the volume of past events <i>i</i> received from <i>j</i> .	The more email messages John has received from Irene, the higher the rate of future email messages from John to Irene.
Transitivity		The tendency of person <i>i</i> to initiate events towards person <i>j</i> , as a function of the volume of past events <i>j</i> received from others to whom <i>i</i> had sent events.	When John observes that people who receive his information provide Irene with info, John's rate of providing Irene with information increases.
Participation shift AB-BY ("turn-receiving")		The tendency of an initial receiver <i>j</i> of an event to, in turn, direct the next event to another person <i>k</i> .	John talks to Mary, then Mary talks to Irene.
Participation shift A0-XA ("turn-claiming")		The tendency of an individual member of the group to take over the conversation that was addressed by <i>i</i> to the group as a whole.	John talks to the group, then Frank talks to John.
Participation shift A0-AY ("turn continuing")		The tendency of a person to keep talking: <i>i</i> first addresses the group and next addresses an individual member of the group.	John talks to the group, then addresses Mary.
Multiplexity		The tendency of person <i>i</i> to continue to initiate events towards person <i>j</i> , as a function of the volume of past events from <i>i</i> to <i>j</i> with a different content or type.	If John has provided Irene with face-to-face project progress updates, John may start to send her email messages as well.
Attribute homophily		The tendency for individuals to initiate relational events to others "like them" (e.g., similar expertise, role, function, tenure, team membership).	John is more likely to communicate with Irene (who is on the same component team as John), than with Peter (who is on another team), even though both teams are part of the same project.

(continued)

Table 3. (continued)

Name	Visualization	Interpretation	Example
High initiator		Dummy, indicating whether a particular individual is exceptionally talkative.	John talks to anyone with a heartbeat, whereas Irene is much more limited in her choice of interactions.
Popularity		The tendency of <i>i</i> to receive relational events, as a function of the extent to which <i>i</i> has been the recipient of relational events in the past.	Everyone wants to talk with Peter. An individual relational event is then more likely to be directed to Peter than to Mary, who is much less talked to overall.
Interteam inertia		The tendency of person <i>i</i> to continue to initiate events towards person <i>j</i> on another team, as a function of the volume of past events from <i>i</i> to <i>j</i> .	The more John has asked Peter, who is on another team, for technical info, the more likely John is to continue this cross-team interaction with Peter.
Interteam reciprocity		The tendency of person <i>i</i> to initiate events towards person <i>j</i> (who is on another team than <i>j</i>), as a function of the volume of past events <i>i</i> received from <i>j</i> .	The more John has provided Irene (who is on another team than John) with information regarding the project, the more Irene will initiate cross-team information sharing between them as well.
Interteam mimicry		The tendency of a person <i>i</i> to initiate a relational event to person <i>k</i> on another team, as a function of the past interaction with <i>k</i> by <i>i</i> 's teammates.	Seeing that his teammate Mary sends Peter (who is on another team) technical information, John starts sending Peter technical info as well.

Sender of the relational event,
 Receiver of the relational event,
 Other individuals
 -----> future events, ———> past events.
 Different shapes indicate different teams.

Given the psycho-social benefits that reciprocity affords and the norms of reciprocity that exist in many social groups, individuals tend to reciprocate interactions (Coleman, 1990). Therefore, we might expect that the higher the volume with which *B* has, for instance, asked *A* for information in the past, the more likely that *A* will ask *B* for information in the near future. A positive parameter signifies tendency towards reciprocity among the team members, a negative parameter

signals that team members avoid (quickly) returning interaction with others.

An SSS that is conceptually related to reciprocity is *transitivity*, which posits that the occurrence of a future relational event from *A* to *B* is influenced by the volume of prior relational events from *A* to other team members (*C*, *D*, *E*, for instance) and prior relational events from them to *B*. For example, if John has gone to Peter in the past for advice and Peter turned to

Mary for advice, John might turn to Mary for advice in the future as well. Transitivity is often summarized by the adage “the friends of my friends are my friends” and is based on the drive for positive interpersonal sentiment; the general argument is that in order to reduce cognitive dissonance, intransitive triads (i.e., the situation where John is a friend of Peter, Peter is a friend of Janet, but John and Janet are not friends) tend to become “balanced” or transitive over time by, for instance, John and Janet becoming friends (Cartwright & Harary, 1956; Heider, 1958; Newcomb, 1968). Repeated interaction between John and Peter and between Peter and Janet signals trust, understanding, positive interpersonal sentiment, and general compatibility of personality or expertise between the members of these two dyads. This in turn signals that it is likely that interaction between John and Janet would be conducive to trust and mutual understanding as well. The higher the volume of past interaction from John to Peter and from Peter to Janet, the more likely we expect a future interaction to occur from John to Janet as well. A negative coefficient is indicative of negative attitudes towards interacting in closed circles, (or, more accurately, triangles). When studying how and when individuals provide others with information, the transitivity SSS can also be understood in terms of “broker-skipping”: if John provides Peter with information who, in turn, frequently provides Janet with information, then John could be inclined to skip broker Peter the next time and provide his information directly to Janet.

Another theoretically interesting application of SSSs is to characterize “participation shifts”: ways in which verbal conversations flow in groups (e.g., in a social setting or in a formal team meeting). Following the work of Goffman (1981), Gibson (2003, 2005) assigned the participants in a conversation the roles of speaker, target, and third party. Over the course of a conversation different group members inhabit these roles, and Gibson categorizes 13 distinct ways in which these so-called *participation*

shifts can happen. Examples include: “John talks to Mary, then Mary talks to Irene” (“turn receiving,” labeled as AB-BY), “John addresses the group, of whom Frank responds to John” (“turn claiming”, A0-XA), “John talks to the group, then addresses Mary” (“turn continuing,” A0-AY), or “John talks to Mary, then Frank talks to John” (“turn usurping,” AB-XA; Gibson, 2003, p. 1342). When analyzing the flow of conversation in a team meeting, significant effects of such SSSs indicate the inclination of the group discussion to display particular conversational patterns. For instance, a positive and significant coefficient for A0-AY (“turn continuing”) would signal that the person who starts a group discussion tends to continue her turn by then addressing a single individual in the group, rather than keeping the discussion at the group level or being immediately responded to. To fully interpret the flow of conversation in a team, a researcher would include multiple participation-shift SSSs into an analysis. Butts’s (2008) analysis of the radio conversations of first responders (police, mainly) immediately after the WTC disaster on September 11, 2001 is an example of an analysis that includes SSSs characterizing several participation shifts. Butts (2008) found the AB-BY (turn receiving) SSS to be positively significant, suggesting the prevalence of a “handing-off” norm, allowing important information to be relayed quickly among the first responders.

So far, we have focused on SSSs where the rate of a relational event is based upon prior occurrences of the same type of relational event. Next, we consider so-called “exogenous explanations” of the observed sequence of relational events in a team; these refer to explanations where the rate of a relational event is based upon any and all factors other than the specific type of relational event itself. These exogenous explanations can be further classified into two categories: relational level and attribute level (see Burt, Kilduff, & Tasselli, 2013; Kilduff & Brass, 2010; Kilduff & Tsai, 2003; for further rationale underlying this categorization).

Relational level exogenous explanations include theories positing that the rate with which a relational event occurs depends on the previous occurrence of *other types* of relational events. For instance, the SSS termed *multiplexity* posits that the rate of a relational event dealing with, for example, goal setting is likely to be influenced by prior occurrences of relational events dealing with, for example, planning. When the coefficient for multiplexity is positive, a relational event of one type tends to be followed by a relational event of another type: team members thus actively communicate about a set of interaction topics, rather than sticking to a single topic. Negative effects are indicative of interaction between two individuals tending to revolve around the same topic over time.

Attribute level exogenous explanations include theories positing that attributes of team members influence the rate of occurrence of a relational event. There are at least two ways in which the attributes of the group members can influence the rate of a relational event: individual attribute level exogenous explanations and shared attribute level exogenous explanations. *Individual attribute level exogenous* explanations consider only the attribute of the team member who is the initiator or the recipient of the relational event. For instance, one might posit that an individual with a high level of expertise on a given task is more likely to initiate relational events associated with backup behavior with *any* of the other team members (irrespective of the individual attributes of the recipients). A negative coefficient would represent a situation where, for instance, team members with the highest levels of expertise tend to initiate the least frequent backup behavior-related interaction.

Another example of an individual attribute is based on the finding that the distribution of communicative acts tends to be highly unequal in closed group settings (Bales, Strodtbeck, Mills, & Roseborough, 1951). Some people are more talkative than others; these talkative members have higher rates of communication

than less talkative individuals. After Bales (1953), we term this SSS *high initiator*; it is simply a dummy of whether someone is considered a high initiator or not. Similarly, a *popularity* SSS could posit that a particular team member is characterized as an exceptionally popular recipient of relational events (i.e., a “high receiver”). This means that we would expect that, all else being equal, this person would receive relational events at higher rates than others.

Shared attribute level exogenous explanations of the rates of relational events take into account the extent to which team members have similar or dissimilar attributes. As an example, consider a multiteam system (MTS) where members are distributed across multiple teams. The SSS *interteam inertia*, posits that the occurrence of an interteam relational event from a member of one team to a member of a different team (within the MTS) is likely to be influenced by prior occurrences of the relational event between them. The *interteam reciprocity* SSS posits that the occurrence of a relational event from a member, *A*, of one team to a member, *B*, of a different team (within the MTS) is likely to be influenced by prior occurrences of the same interteam relational event initiated from *B* to *A*. The presence of these two SSS in an MTS would reflect a stable (interteam inertia) and responsive (interteam reciprocity) sequence of relational events. A plausible hypothesis would be that the rates of interaction among members of the same team are higher than the rates of interaction between members of different teams (“team membership homophily”). If the relational event is information sharing, this would indicate that information is shared at higher rates within teams than across teams, which could have important implications for the diffusion of information across the MTS as a whole (especially when the differences in rates become substantial).

Shared attribute level exogenous explanations do not need to be confined to the two

actors engaged in the relational event. Consider, for instance, a scenario where member *A* from one team initiates interteam relational events with member *B* from another team in the MTS. Based on an SSS we term *interteam mimicry*, we posit that other members who are on *A*'s team (and hence share with *A* the attribute of team membership) are then also more likely to initiate relational events with member *B* from the other team; in other words, *A*'s prior interteam interaction with *B* is mimicked by *A*'s team members.

Multiple SSSs

Many more SSSs can be defined, and researchers have included many other SSSs in their research (Brandes et al., 2009; Butts, 2008, 2012; Quintane, Conaldi, Tonellato, & Lomi, 2014; Quintane, Pattison, Robins, & Mol, 2013). As an example of how multiple SSSs can be considered together, one could formulate a theoretical model in which the rate of information-sharing among members in an MTS: (a) increases with habit (i.e., team members tend to keep sharing info with the same others, *inertia*), (b) increases with the tendency of sharing information back (*reciprocity*), but (c) this latter effect being even stronger among members within the same team rather than between teams (*intrateam vs. interteam reciprocity*), (d) increases if the recipient is a formal leader (*individual attribute level*, recipient is a leader), and (e) increases if both members are nonleaders (*shared attribute level*, sender and recipient are both nonleaders). One would test such a model by parameterizing the rate of interaction as in Equation (1) and then testing for statistical significance of the coefficients corresponding to these five SSSs and inspect their signs (as one would do in a traditional regression analysis).

The choice of relevant SSSs for teams varies based on the teams' levels of skill differentiation, authority differentiation, and temporal stability (Hollenbeck et al., 2012). *Ceteris paribus*, we would expect teams that are

temporally stable to be more strongly influenced by the inertia and reciprocity SSSs. Similarly, as team members build a long history of interaction, we would expect that multiplexity would also likely be high in this type of team (because longer lasting interaction also affords team members with extended exchange opportunities among them). Homophily-based SSSs are also likely to be low (or negative) in long-lasting teams with little or no turnover, because over time interaction may be more likely to occur across all members of the team, regardless of whether they are homophilous in rank, role, or expertise. In teams with high levels of task and authority differentiation, on the other hand, we would expect homophily-based SSSs to be high, *ceteris paribus*, as communication becomes confined to take place between team members with similar skill and authority. In such teams, with a clear division of task and expertise, the set of participation-shift SSSs might be of particular relevance, as they capture how interaction shifts occur among team members in an organized manner.

Memory

Our theoretical model posits that the past volume of one or more SSSs influences the rate with which a future relational event will occur. This suggests that the occurrence of a relational event is just as much influenced by a previous event that happened recently as by one that happened a long time ago. This may not be realistic. If team members received valuable information from other team members, they may be much more likely to return the favor in the very near, rather than the very distant, future. In general, one might conjecture that the memory of recent relational events should generally be more influential than those that occurred in the more distant past. Within a relational event network framework, a researcher can accommodate the diminished influence of preceding events by specifying a decay function of the weight of past events. A

straightforward decay function is specified by a *half-life period* (Brandes et al., 2009). The half-life period (or simply *half-life*, as we will term it)—originally developed by Rutherford in 1907 to describe radioactive decay in physics—is the duration of time after which the influence of a prior relational event on the rate of a future relational event is halved. The shorter the half-life, the faster past events lose their influence on the present and the more strongly the near future is determined by what happened in the immediate past. This can, potentially, lead to more volatile interaction dynamics within the team. On the other hand, the longer the half-life, the longer past events will continue to have an effect, which likely leads to more stable and consistent interactions within the team. In essence, the half-life represents the memory span that team members operate on: shorter half-lives represent shorter memories (cf. Card, Moran, & Newell, 1986) and shorter path dependencies.

It is worth noting that there are many other ways to specify memory decay functions as well (besides assuming a half-life). A comprehensive, systematic, overview of the various decay functions that have received traction in the psychological literature is provided by Chechile (2006), several of which are compatible with the idea of half-life. Chechile's research suggests that, although monotonically decreasing memory functions (such as the half-life) make sense, more elaborate functions may describe actual intrapersonal memory decay more accurately. It is fairly straightforward to implement many of Chechile's decay functions in the statistical model that we will present in Part III of this paper. Theories of team process are by and large agnostic to the exact specification of memory decay curves and, as a consequence, very little theoretical guidance is available to the researcher to choose an appropriate decay function. Utilizing a half-life memory function serves as a useful stepping stone to the more sophisticated approaches to modeling memory presented by Chechile (2006).

To see how the notion of a half-life could be integrated into processual thinking, consider Brett, Shapiro, and Lytle's (1998) study of conflict spirals in negotiations. Brett and her colleagues found that the norm of reciprocity can be "broken" by one individual in a conflict by repeatedly not reciprocating contentious communications (i.e., a negative reciprocity SSS). Using the concept of a half-life, one could test just how long team members need to refrain from reciprocating a contentious communication, until the conflict vanishes from active consideration. One approach a researcher can take is to compare the fit of models with different half-lives (or otherwise differently shaped decay curves) and thus empirically test how long past events retain their effect on future communication. Quintane et al. (2013) used a variant of this approach to study how long-term versus short-term interaction patterns might create stable interaction sequences in organizational teams. Their relational event model included every SSS twice: a short-term version (measured by letting the past only include the interactions of the last 24 hours) and a long-term version (measured by letting the past consist of the interactions of the last 4 months). Although their choice of what constitutes short versus long term is arbitrary, their approach sheds light on the extent to which long-term versus short-term path dependencies might shape future interaction.

Theorizing about outcomes

SSSs explain how team members shape their interactions with one another. SSSs can also be used to aid the development of normative models of team process: explaining how team members *should* form relations with one another. The analytic approach proposed here provides an opportunity to test hypotheses about how the SSSs that characterize a relational event sequence in a team influence team outcomes.

When SSSs are entered into a statistical model of the form (Equation 1), the statistical

analysis provides estimates of the extent to which the rates of the relational events between dyads in a team are characterized by each of the SSSs. When multiple teams are studied, these estimates can be computed for each team individually.¹ It is likely that one would find variability in the extent to which different SSSs fit their sequence of relational events observed in each team and, one would undoubtedly find variability in the performance of the teams as well. The key theoretical question then becomes whether teams where certain SSSs explain their sequence of relational events show higher performance than teams where other SSSs explain their sequence of relational events. For instance, following the rationale that reciprocity in teams leads to more effective coordination which, in turn, leads to higher performance, one might hypothesize that teams with a positively significant reciprocity SSS are more likely to have higher performance than teams without a temporal tendency towards reciprocated interaction.

Related approaches

Before we describe the statistical model that allows one to test whether a hypothesized set of SSSs is indeed predictive of a sequence of relational events, we briefly describe some other related approaches. The oft-cited work of Robert Bales has been particularly important for the field (Bales, 1950a, 1950b; Bales & Strodtbeck, 1951; Bales et al., 1951). Integral to his approach was the Interaction Process Analysis (IPA) behavioral coding scheme, consisting of 12 major categories across four sections. Although Bales used his methodology to develop a linear phase model to describe the discussion stages that groups progress through, his main contribution was his coding scheme, which continues to be used today (e.g., Jones, Carter-Sowell, & Kelly, 2011). For our approach, Bales' 12 categories could be used to code types of relational events, so as to distinguish, for example, "giving a suggestion"

from "giving an opinion" as separate types of relational events (Bales, 1950b).

Bakeman and colleagues (2000; Bakeman & Gottman, 1997; Bakeman & Quera, 1992, 1995) developed another observation and coding scheme. Like that of Bales, Bakeman's coding scheme can be used to define relational event types. In addition, some of his techniques can measure entire event streams, including the timing of events. Bakeman developed an extensive set of techniques to check data collection quality and used log-linear models in data analysis. Statistically, his methods focus on summarizing the event sequence and on the transitions from one event type to the next, and it appears well worth extending them further with the kind of statistical analysis that relational event models offer, so as to gain further insight into the structural (i.e., networked) characteristics of relational event sequences. A recent application of Bakeman's approach to organizational teams is that of Klonek, Lehmann-Willenbrock, and Kauffeld (2014) who explored the idea that change agents, who communicate necessary changes to organizational employees, can themselves trigger resistance to change in change recipients. Focusing on the dynamic interaction process between change agents and recipients, they found that "autonomy-restrictive" utterances by change agents elicit "sustain talk" in recipients, which, in turn evokes autonomy-restrictive agent behavior. A relational event model could add to this type of analysis by analyzing interaction differences between change agents, the speed with which resistance versus supportive communication unfolds, and by uncovering the interaction patterns that might be more or less conducive to triggering (or overcoming) resistance.

Setting aside content, Dabbs and Ruback (1987) developed an approach to measure content-free interaction in a group, specifically focusing on the way talking (e.g., amount of talking, vocalization) evolves in a group. The authors describe coder-free ways to capture data and provide several case studies as examples.

Their empirical work does not build on a unifying statistical framework, but employs a wide range of statistical tools, in a largely exploratory fashion. The participation-shift SSSs offer potential extensions to their approach.

An approach that explicitly takes into account the time in between events is the work by Magnusson (1996, 2000, 2005), who developed a machine-learning approach (known as THEME) to detect specific patterns of event sequences (called “T-patterns”). His approach has been used in a wide range of scientific fields, including in the study of organizational teams (Ballard, Tschan, & Waller, 2008; Stachowski, Kaplan, & Waller, 2009; Zijlstra, Waller, & Phillips, 2012). The THEME approach is to search for so-called “hidden patterns” that emerge from the data and that occur more frequently than would be expected by chance alone—typically, a few dozen such patterns will be found in an analysis. The approach is quite different from ours, as it is descriptive and exploratory, whereas the relational event model is explanatory and inferential. However, a researcher can certainly combine both approaches. The testing of theoretically grounded hypotheses based on SSSs can be accompanied by a data driven exploratory phase that retrieves longer, typically more complex, behavioral patterns of interest. These patterns could then inform new theoretical explanations that could then be tested in a further round of theory driven models.

Finally, a powerful approach to analyze sequential event data is to use Markov models; two recent studies include Poole and Dobosh (2010) and Stadtfeld and Geyer-Schulz (2011). In a Markov model, each subsequent dyadic event is modeled as a function of the present, which is assumed to contain all the relevant information one would need to know about the past. Hence, information about the order of the sequence of relational events that lead to the present is not retained. Markov models make stringent assumptions, including the assumptions of homogeneity (rates are the same for all

dyads and across time), but they are statistically straightforward and easily interpretable.

Part III: A statistical model to study team process as relational events

Central in our approach is the *relational event*, for which we can distinguish, at a minimum, a sender, a receiver, and the order or time at which the event occurs. Senders and receivers can be individuals or collectives. The set of potential senders need not be the same as the set of possible receivers—for example, in an analysis of team members giving each other directions on which tasks to perform, one could argue that team leaders will be among the senders of such events, but may not be potential receivers.

The analysis of event data, also known as *event history analysis* or *survival analysis*, is an established area in statistics and social science—for excellent overviews see Box-Steffensmeier and Jones (1997) and Lawless (2003). The relational event statistical framework builds on these established models, but adds to them an ability to incorporate quite complex structures of historical dependence among observed relational events among a network of actors. Having observed a sequence of N events $event_1$ through $event_N$, we assume that each $event_i$ depends on the past history of all events up to $event_i$. Exactly how one believes it depends on the past is defined by which SSSs are included in the model. The heart of the model is the so-called hazard rate, mathematically defined as the event rate at time t given that the event hasn't happened before that time. The rate at which events take place can (and generally will) vary over time in a team, but we assume it remains constant between $event_i$ and $event_{i+1}$ (but it is allowed to differ from the rate between $event_{i+1}$ and $event_{i+2}$). This generally plausible statistical assumption allows us to write the rate as an exponential function, as in Equation (1). A detailed technical description of the model can

be found in Butts (2008), who developed the original statistical model. An important extension to the model is provided by Brandes et al. (2009), who add the half-life to the model. Several additional useful extensions are obvious, one of which is to include the potential designation of certain events as “exceptional”: such events might be exempt from the half-life and even be given extra influence on later events. An example could be a personal conflict or dominance threat that lingers on the mind of the recipient longer than more recent “ordinary” events. Indeed, as Ballinger and Rockmann (2010) argue, some past events can become “anchors” that keep exerting their influence on relationships far into the future.

Because the model parameterizes the rates of relational events, it directly captures differences in pacing within the team. For example, if reciprocity and inertia are significant and positive, we can expect faster exchanges (i.e., higher rates) between those individuals who have a more voluminous shared history than between team members with a leaner interaction history. We can also plot the rates graphically, showing how they evolve over time in the team and how they differ across dyads.

In essence, it helps to think of the model as predictive of the *next event*: if one were to watch the movie of all interactions and would then suddenly stop the projector: exactly when would you expect the next event to happen and who will be the sender and who will be the receiver? In essence, this is what the model captures and a straightforward way to establish statistical fit is to enumerate the proportion of correctly predicted next events.

Part IV: An empirical example

To illustrate how a relational event network can be analyzed, we provide an example involving a multiteam system (MTS) consisting of two teams of two individuals each. The data were collected as part of a laboratory experiment where the MTS had to maneuver a humanitarian aid convoy

through a hostile territory, using a computer platform based on the real-time simulation game “World in Conflict.” Although the two teams worked in different regions, their main MTS task was to *jointly* move the convoy safely, a task for which they had to share information across all four MTS members and coordinate their joint actions. The communication among the MTS members was computer-mediated (using voice and text), which allowed us to access server logs containing information of the sender(s), receiver(s), and time of each interaction. The purpose of the example is two-fold. First, it provides an illustration of how one interprets the effects of SSSs in an empirical context. Second, the example illustrates the use of a simulation platform which provides researchers with the opportunity to capture and time-stamp all interaction among the participants. This type of temporally fine-grained data can be used for studies of multiteam systems, like we do here, but is equally viable to other team settings (Bjørnstad, Fostervold, & Ulleberg, 2013; Davison, Hollenbeck, Barnes, Slesman, & Ilgen, 2012; Lanaj, Hollenbeck, Ilgen, Barnes, & Harmon, 2012).

In this example we focus on two MTSS. We hypothesized *inertia* and *reciprocity*: we expected that it would not take long for the communication exchanges to become routinized and inertia and reciprocity are hallmarks of routinized communication patterns. In addition, we hypothesized negative *interteam reciprocity* (i.e., that team members might more favorably respond to communication from a member of their own team than to that from members of the other team) and *interteam mimicry* (i.e., that cross-team communication by one member of a team might motivate his/her colleague to subsequently engage in cross-team communication as well). Table 4 summarizes the findings of the statistical analysis.

For the first MTS (MTS-1), the *inertia* parameter was positive. A separate analysis conveyed that inertia set in fairly quickly, in the beginning the MTS members tried out various

Table 4. Summary of empirical findings.

	MTS-1	MTS-2
Inertia	+	+
Reciprocity	+	+
Inter-team reciprocity	ns	–
Inter-team mimicry	+	–

Note. “+” represents a statistically significant positive effect; “–” represents a statistically significant negative effect; “ns” represents a statistically nonsignificant effect. Although the statistical analysis provides us with actual numeric parameter estimates, in this example we only focus on the sign of the parameters.

communication patterns, but fairly soon they settled into a pattern.² MTS-1 also showed a positive *reciprocity* parameter, which indicates a norm among participants to respond to incoming communications. Reciprocal communication was acted on as a global norm: response rates were not different within teams versus across teams; hence the nonsignificant parameter for *inter-team reciprocity* (in combination with the significant, positive, *reciprocity* parameter). Also *inter-team mimicry* was positive, which shows that the members of a team followed their teammate’s example of maintaining cross-team communication. Overall, the SSSs describe a situation in which individual MTS members responded rapidly to all others, displaying no communication preference for teammates versus members of the other teams, and maintaining a fairly stable speed and structure of communication that established itself fairly quickly.³ Although the MTS consisted of two teams with somewhat separate mandates, they operated as a fully connected four-person network, and almost like a single team.

Another MTS (MTS-2), taking part in the same simulation, initially operated very much like MTS-1 and quickly settled into a routine (positive *inertia*) where everybody communicated evenly with everybody else and everyone quickly and positively responded to any interaction (positive *reciprocity*). But about one third of the way into the observation period, the MTS members changed their modus operandi,

leading to the *inter-team reciprocity* parameter turning negative: the rate by which members *within* a team would go back and forth between each other did not change, but response between the members of *different* teams slowed down significantly. In addition, *inter-team mimicry* became negative, indicating that the more one team member maintained interaction with the other team, the less other teammates were inclined to do the same. The result of this shift is that MTS-2 started to reorient itself into a chain-like structure: communication within teams remained consistently swift and between all team members, while communication between teams became mainly channeled through a single gatekeeper per team. Communication rates within the respective teams were highest, between the two gatekeepers a bit lower, and were lowest between the nongatekeepers. Reciprocity was no longer the norm between the teams, but it did remain strong within the teams. Overall, these SSSs characterize highly differentiated interaction tendencies within MTS-2 and highlight how MTS-2 dynamically restructured itself freely from a fully connected four-person network into a chain structure.

Although some of these findings could also be established with more traditional research methods, the strength of the relational event approach is that we can precisely analyze the evolution of the interaction rates and how they are driven by hypothesized parameters. Although the example has been brief and would normally be part of a larger, more in-depth, analysis, it highlights how thinking in terms of relational events addresses the challenges of process research that we discussed in the beginning of this paper. Clearly, MTS-2 did not show homogeneity over time and analyzing it as time-homogenous would have made researchers overlook how the MTS reorganized itself. In addition, MTS-2 is an example of interaction evolving differently in different parts of the team (in this case, along team membership). Whereas a researcher could effectively aggregate effects across MTS-1, such an approach would miss essential characteristics of

MTS-2's process over time. Since we had no way of knowing beforehand whether an MTS would reorganize itself and, if it did, when it would do so and at what pace that would happen, we would most likely have missed much of the dynamics if we had sampled the interaction at, say, two or three times during the MTSs existence. Moreover, by only measuring a few times, we could not have established that MTS-1 remained stable throughout: all we would be able to tell is that it looked quite similar at each measurement point, but that says little about what could have happened in between the measurement points. Finally, the analyses highlight a few temporal notions: interaction rates (which changed strongly over time for MTS-2) and path dependence (which was high for MTS-1 but less so for MTS-2). An obvious next step would be to repeat such an analysis for a larger number of teams, which would then allow us to establish insight into which process dynamics are conducive to good (or poor) performance. For example, we might test whether MTSs that routinize faster than others perform better, whether the speed with which an MTS restructures itself affects its future performance, whether leaders maintain higher rates of interaction than nonleaders, whether routinization occurs faster/slower within or between teams, whether MTSs that operate on longer interaction memories, (i.e., that operate on longer half-lives) perform differently from those with shorter memory, and so on.

Conclusion

In our opening, we pointed out that while much progress has been made in detailing different types of team processes, empirical evidence of their predictive validity is generally underwhelming and we pointed to the need for a more specific temporally rich theoretical formulation of process. In 1975, J. Richard Hackman and Jim Morris published a review of research on small groups, and noted that "part of the difficulty in understanding the relationship between group interaction and group effectiveness has to

do with the nature of existing methodological and conceptual tools" (Hackman & Morris, 1975, p. 4). We expect this critique is still true today.

In this paper we have put forward a set of requirements that, we believe, serve to develop theory and methodology that allows research on team process to make a sizeable leap forward: disaggregation of team process over time and across team members, imbuing our theories and analyses with more temporal constructs, and focusing our theories and designs explicitly on processes in continuous time (with local, dyadic, interaction as the fundamental building block). We then advanced a dozen theoretical mechanisms (called SSSs) by which interaction among individuals in a team can evolve over time. Of course, many more SSSs can be (and have been) proposed. Our aim was not to be exhaustive, but to highlight a way of thinking temporally about team process that might inspire researchers to develop their own temporally based models of team process.

From a statistical point of view, performing a relational event analysis need not be hard. Freely available software exists (Butts, 2012) and some versions of the model can even be estimated with standard statistical software (e.g., Quintane et al., 2014; Quintane et al., 2013). In addition, data has become easier to acquire. An analysis along the lines of what we propose in this paper only requires data that capture who interacts with whom at what point in time (or in what order), and, ideally (but not necessarily) about what. Preferably (but, again, not necessarily), a researcher would also collect some performance/outcome data, so that it becomes possible to test whether certain temporal interaction patterns are associated with differential levels of performance (of groups, the individuals in the groups, or systems of groups). Since there is often no sound theoretical argument as to exactly when or for how long an outcome is expected to occur, ideal data would include temporal performance data as well. Access to these types of data is getting

easier. Experiments in the lab are often video-recorded and technologies are making it easier to annotate the video to acquire time-stamped relational data. The volume of relational event data is going to continue to grow dramatically as an increasing amount of our actions, interactions, and transactions occur over digital networks. Indeed the increasing prevalence and promise of even more digital time-stamped data has been a major motivation for the recent interest in the development of relational event modeling techniques.

Once upon a time, researchers believed in the importance of understanding team dynamics, but were hindered by dominant conceptual views of the nature of group interactions. And so, once upon our time, we present a case for this hindrance, propose an alternative conceptualization, and detail an analytic apparatus with the potential to advance knowledge on team dynamics one step at a time. Analyzing team process as relational events allows researchers to hypothesize and test fine-grained theoretical mechanisms and, perhaps even more importantly, derive specific findings that can inform the further development of more explicit time-sensitive theories.

Notes

1. Because the rates are defined at the dyadic level and are observed in continuous time, their effective sample size can increase quickly. As a result, an event sequence of only a single team generally provides ample data to statistically test a model with a fairly extensive set of SSSs.
2. One informative way in which such an analysis can be performed is by analyzing the data using a “sliding window,” which is a simple approach that shows how the parameters evolve over time.
3. An additional analysis suggested that there was some differentiation in communication speed across the formal roles of the MTS members.

Author's note

The views, opinions, and/or findings contained in this manuscript are those of the authors, and should

not be construed as an official Department of the Army position, policy, or decision, unless so designated by other documents.

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